

Review on Heart Sound Analysis Technique

U. More Monali and R. Shastri Aparana

Abstract Heart auscultation (the interpretation by a physician of heart sounds) is a fundamental activity of cardiac diagnosis. It is, however, a difficult skill to acquire. So it would be convenient to diagnosis the failure using some monitoring techniques. This paper reviews different signal processing technique for analyzing Heart Sound (HS) Vibration signals which is mainly used to diagnose these diseases. Conventional methods for fault diagnosis are mainly based on observing the amplitude differences in time or frequency domain such as Fourier Transform (FT), Short Time Fourier Transform (STFT), and Wavelet transform. This paper includes Spectral analysis method of heart sound by using autoregressive power spectral density (AR-PSD) for discriminating normal and abnormal HS, another method to diagnose heart sound such as Wavelet packet analysis and classifiers like Hidden Markov Model (HMM), Artificial Neural Network (ANN).

Keywords Fault diagnosis • Heart sound • STFT • Wavelet transform • Autoregressive power spectral density • HMM • ANN

Introduction

Auscultation, listening to sounds emanating from human organs, is a primary routine for screening and diagnosing many pathological conditions of the heart. Heart sound signal contains physiological and pathological information, which is

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related to each part of heart (atrial, ventricular, cardiovascular, and valvular function). With the improvement of domestic living standard, numbers of patients with heart disease are increasing rapidly. The heart disease is associated with living conditions, such as coronary heart disease (angina pectoris, myocardial infarction) and hypertension [1]. It becomes more and more difficult to recognize and diagnose heart sound in traditional auscultation way, because of limitation of human hearing sensitivity and auscultator’s clinical experience. Now, heart disease is not the “patent” of elder, it also threatens many striplings’ health. How to find symptom and know the incidence status in advance, is necessary to prevent and diagnose heart disease [1]. Heart sound and murmurs are of relatively low intensity and is band limited to 10–1000 Hz. The mechanical activities of the heart during each cardiac cycle produce the sounds, which are called heart sounds. The factors involved in the production of heart sounds are as follow:

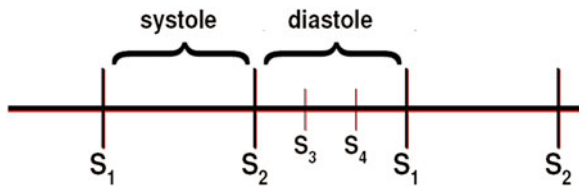
- (1) The movement of the blood through the chambers of the heart.
- (2) The movements of cardiac muscle.
- (3) The movement of the valves of the heart [2].

Human heart generates four sounds during its activity for one cardiac cycle. These sounds identified as S1, S2, S3, and S4 are not all audible. Figure 1 shows four heart sound S1, S2, S3, and S4 with systole and diastole.

S1 is generated at the end of atrial contraction, just at the onset of ventricular contraction. S1 can be heard obviously in the interval of the fifth rib which lies in the midline of left clavicle. The main feature of S1 is low tone and long time lasted. S2 occurs during ventricular diastole and can be heard clearly at the auscultation region between aortic valve and pulmonary valve. In contrast with S1, it has characteristics of high tune and short time lasted. S1 and S2 contain important information of cardiac sounds auscultation [3].

In recent ten years, with the rapid development of computer hardware and digital signals processing techniques, heart sound could be easily recorded and analyzed, the research [2] on automatic heart sound analysis showed its new tendency. Most of these researches were concerning on the characteristic extraction by frequency analysis method includes FT Fourier transform), Short time Fourier transform (STFT), Continuous wavelet transform (CWT), etc. Some other researchers were on how to extract of the heart beat from weeping noises of a baby and noise cancellation by an adaptive filtering method.

Fig. 1 Location of heart sound in cardiac cycle



Analysis Techniques

STFT

(1) Fan and Brooks [4], proposed *Detection of Hypovolemia Using Short-Time Fourier Transform Analysis of S1 Heart Sound*. The goal is to detect hypovolemia as revealed by changes in the S1 and S4 heart sound. Heart sounds early in systole (S1 and S4) are sensitive to changes in blood volume in the heart chambers. Thus, the purpose of this study is to investigate whether changes in acoustically monitored heart sounds during anesthesia can be used to detect hypovolemia. In this paper author describe the use of the STFT to represent S1 sounds, and the use of signal processing methods to extract detection statistics from the modulus of the STFT. This method can be summarized in four steps: Waveform, STFT, Band-limited energy signal (BES), and Quantized pulse train signal (QPT) Classification.

Band-Limited Energy Signal (BES). The short-time nature of our STFT (small L) implies poor spectral resolution, so only frequency-averaged quantities can be reliably estimated. Since S1 and S4 normally have most of their energy below 200 Hz, we next calculate a band-limited energy signal, denoted BES, at short-time interval l , as

$$BES(l) = \sum_{k=i1}^{i2} |X(l, k)|^2$$

where, the frequency indices corresponding to 20 and 200 Hz, respectively.

Thresholding in amplitude. Again based upon the observed audible changes, our major goal is to detect the extent of a “split” sound in *S1*. Thus we next generate a quantized pulse train signal, QPT (l), from BES (l), by means of a threshold.

Classification statistic based upon interpulse interval distribution. After obtaining the QPT signal for each heart sound, we have transformed a noisy S1 waveform to an energy-based signal which estimates when the sound is “on” and when it is “off”.

The Fig. 2 shows Histogram of the interpulse interval distribution of all expiration S1 sounds during 20 s epochs before, during, and after the hypovolemic episode. It seems that interpulse interval statistic seems promising as a discriminator of the hypovolemic state. In addition, we noticed the clear presence of a small but perhaps significant number of S4 sounds during expiration during normovolemia but not during hypovolemia. The presence of the *S4* sound can easily be seen in the *QPT* signal.

Advantage. STFT may provide us with a tool to objectively observe the extent of splitting of S1 heart sounds.

Disadvantage. STFT has problem of fixed resolution. Also it is not good to analysis second heart sound S2 as good as S1.

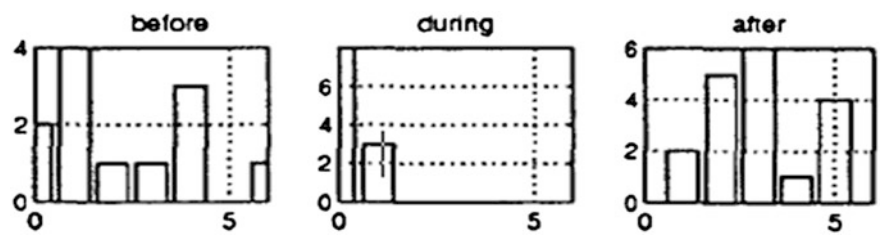


Fig. 2 Histogram of the interpulse interval distribution of all expiration S1 sounds during 20 s epochs before, during, and after the hypovolemic episode

(2) Vikhe and Nehe [2], proposed “Heart Sound Abnormality Detection Using Short Time Fourier Transform and Continuous Wavelet Transform” in which analysis of the first (S1) and second (S2) heart sound of the Phonocardiogram signal (PCG) using STFT and CWT. The STFT combines traditional time domain and frequency domain concepts into a single time–frequency framework. The frequency content and time duration of S1 and S2 can be determined by the STFT without difficulties. The second heart sound S2 consists of two major components A2 and P2. The time delay between them is very important for the medical diagnosis. With STFT it is impossible to determine the time duration between A2 and P2 which plays vital role in diagnosis of the PCG signal. This drawback of the STFT is over come using CWT. The time delays between A2 and P2 have been measured using CWT.

Experiments are performed on normal and pathological PCG signals. Frequency contents of S1 and S2 of PCG as well as time duration of them have been measured using STFT. Split between A2 and P2 have been measured using CWT.

This research shows for the normal heart, S1 includes a single frequency spectral component of energy and the duration of the sound is less in the range of 0.04–0.15 s. For the normal heart, S2 represents a uniform frequency spectral component of energy and the duration of the sound is less in the range of 0.03–0.12 s The magnitude of the energy components of normal heart S1 is higher than that of S2. But in case of pathological, there are more chances of S2 sound energy components to have larger magnitude than that of S1. Similarly, CWT is applied to normal heart sound and abnormal heart sound and result in splits is as follows (Table 1).

Advantage. Frequency content of S1, S2 can be easily measured using STFT, CWT.

Disadvantage. Split between A2 and P2 is not measured with STFT accurately.

Table 1 Split time for normal and pathological conditions

Types of signals	Normal	Aortic stenosis	Pulmonic stenosis	Atrial septal defect
Split (ms)	24	43	48	50

Wavelet Transforms

(1) Vikhe and Hamde [5], proposed “*Wavelet Transform Based Abnormality Analysis of Heart Sound*”. This paper is concerned with the analysis of the first (S1) and second (S2) heart sound of the (PCG) using Discrete Wavelet Transform (DWT) and (CWT). The second heart sound S2 consists of two major components A2 and P2. The time delay between them plays very vital role in medical diagnosis. DWT has been used to determine the best split between A2 and P2 of the second heart sound. Frequency component of each heart sound is determined using DWT. Normal heart sound S1 and S2 has frequency range 0–125 Hz and 125–150 Hz, respectively, but in pathological cases such as Aortic Stenosis, Pulmonic Stenosis, Atrial Septal Defect frequency range exceed to 250–500 Hz.

Using DWT it is impossible to determine the time split between A2 and P2 which plays vital role in diagnosis of the PCG signal.

This drawback of the DWT is over come using CWT. The time delays between A2 and P2 have been measured using CWT. It is observed that the time delay between A2 and P2 is less than 30 ms for normal case and it is greater than 30 ms for pathological cases.

Advantage

- (i) Window size is variable
- (ii) It can handle the point discontinuity.

Disadvantage

- (i) It does not handle curve discontinuities
- (ii) Wavelets do not supply good direction selectivity

2) Using Wavelet and Hidden Markov Model

Lima and Barbosa [6], proposed “Automatic Segmentation of the Second Cardiac Sound by Using Wavelets and Hidden Markov Models”. This work is concerned with the segmentation of the second heart sound (S2) of the (PCG), in its two acoustic events, aortic (A2), and pulmonary (P2) components. An automatic technique, based on discrete wavelet transform and hidden Markov models, is proposed in this paper to segment S2, to estimate the order of occurrence of A2 and P2 and finally to estimate the delay between these two components (split). A discrete density hidden Markov model (DDHMM) is used for phonocardiogram segmentation while embedded continuous density hidden Markov models are used for acoustic models, which allows segmenting S2. The main objective of the work described in this paper was to develop a robust segmentation technique for segmenting the phonocardiogram into its main components.

Advantage. HMM can perform well not only in segmenting the PCG in its main components but also in segmenting the components of the main components

allowing automatic diagnosis related with abnormal order of appearance of the components of the main PCG sounds.

Disadvantage. The performance of the method degrades significantly in severe murmurs, especially in aortic and mitral regurgitation.

DWPA: Discrete Wavelet Packet Analysis

A-Naami et al. [7], proposed Identification of Aortic Stenosis Disease using Discrete Wavelet Packet Analysis. This work includes wavelet packet transforms in detection of an Aortic Stenosis (AS) using heart sound data. The discrete wavelet packet analysis utilizes both the low frequency components, and the high frequency components. From these frequency components and using entropy based criterion, a method for choosing the optimum scheme for the identification of AS Disease is developed.

Entropy is a common concept in signal processing. Classical entropy-based criteria describe information-related properties for an accurate representation of a given signal. There are many entropy criteria among them: Shannon entropy, energy entropy, norm entropy, and threshold entropy. In this study, norm entropy is used to extract some features from the PCG signals.

The procedure followed in the identification of aortic stenosis disease can be divided into three processes described as,

- (1) A PCG signal is to clean it from noise associated with PCG systems. Noise is caused by breast sounds; contact of the stethoscope with skin, ambient noise that may corrupt the heart sounds. The data is filtered with high-pass Butterworth filter to eliminate noise. The Butterworth filter is selected because it has the least steepness of the amplitude response in the transition region.
- (2) The DWPT is used to extract features that can be useful in the classification stage. The wavelet base Daubechies 'db4' is used since it has oscillations very similar to those of a PCG signals.
- (3) The norm entropy-based criterion is used for the classification of PCG signal.

In this method, Frequency is divided into different subbands and for each subband entropy is calculated. If E_1 is larger than E_2 and both are larger than E_{12} and E_{21} , then the heart sound signal is normal. If E_1 is larger than E_{12} and both are larger than E_2 and E_{21} , then the heart sound signal has the symptom of aortic stenosis disease.

Advantages. The DWPA utilizes both the low frequency components, and the high frequency components.

Limitation. The number of data is limited and more is needed to validate the proposed criteria.

Using Autoregressive Power Spectral Density

Wang and Zhang [1], proposed heart sound analysis technique based on Autoregressive Power Spectral Density for discriminating normal and abnormal Heart Sound (HS). Digital stethoscope was used to collect HS and transmitted into computer by USB interface, so as to store, display and analysis. Practical cases of normal/abnormal HS analysis are demonstrated to validate the usefulness and efficiency of the proposed method.

- (1) Initially, using digital stethoscope to collect high-quality sounds, and then preprocessing them preliminarily;
- (2) Second, AR-PSD analysis method was used for discriminating normal and abnormal HS.

The corresponding frequency range of the normal and abnormal AR-PSD are significant difference, representing them by simple curves and digital parameters, it provides a new analytical method to a variety of quantitative evaluation of heart murmurs. The analyzing of normal/abnormal heart sound case verifies the validity of the method.

Figure 3 shows a scatter gram 20 normal and 20 abnormal HS, their parameters distributed in different obvious areas, So, it may provides a novel idea to recognize normal and abnormal HS.

Advantage. Simple to analyze and capable of representing stationary as well as nonstationary signals.

Disadvantage. Difficult to choose appropriate model order.

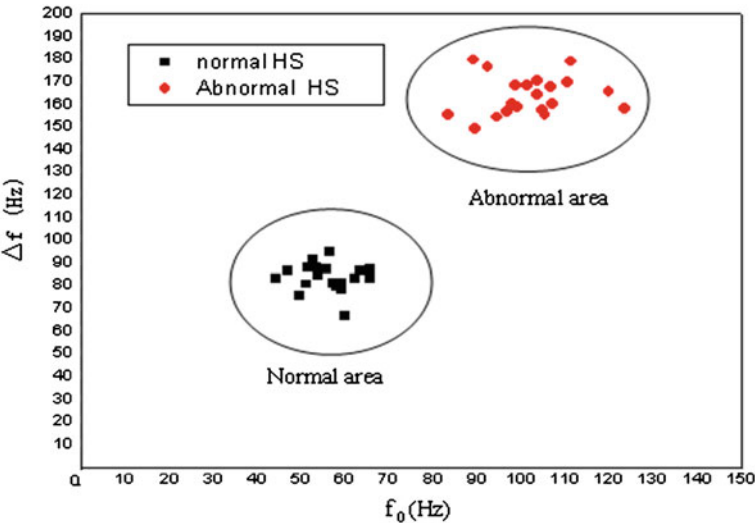


Fig. 3 Scatter gram of f_0 and Δf

Artificial Neural Network

Omid mokhlessi, Naser mehrshad, Hojat Moayed Rad [8], proposed “Utilization of 4 types of Artificial Neural Network on the diagnosis of valve-physiological heart disease from heart sounds”. This work includes sound heart recognition for diagnosing heart disease with four type of Artificial Neural Network (ANN). Here they develop a simple model for the recognition of heart sounds, and demonstrate its utility in identifying features useful in diagnosis. They then present a prototype system intended to aid in heart sound analysis. Based on a wavelet decomposition of the sounds, feature vectors are formed and ANNs finds use in classification of Heart valve diseases for its discriminative training ability and easy implementation. four type of ANN which used for this approach are Multilayer perception (MLP), Back Propagation Algorithm (BPA), Elman Neural Network (ENN), and Radial Basis Function (RBF) Network. Using these ANN classifiers would appeared ability of classifying heart disease and will be shown an accuracy of 81.25 % for MLP, 87.17 % for BPA, 91.59 % for ENN, and 96.42 % for RBF was achieved.

The results demonstrate that the RBF can detect heart diseases with higher Diagnosing accuracy and have best.

Training performance than other ANNs, While, ENN extracts temporal contents from the whole signal epoch after epoch and may support for productive behavior or support inference. Besides, BPA can announce heart diseases with lower Neurons numbers; have best MSE quantity than others.

Conclusion

In this paper, we have reviewed and analyzed different signal processing techniques used for heart sound abnormality detection. We observed that each of the signal processing methods has an advantage to diagnose particular heart disease. Initially, STFT has been used for diagnosis but because of limitation of fixed resolution wavelet transform is used later. Other methods-mentioned such as Wavelet Packet Analysis, Autoregressive power spectral density, HMM, ANN also has own advantages such as utilization of low and high frequency component, capable of analyzing stationary and nonstationary signals. Because of some limitation of human hearing sensitivity and auscultator’s clinical experience signal processing technique plays important role in diagnosis of heart sound abnormality.

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